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A Survey of Methods and Architectures for Early Detection and Segmentation of Diabetic Foot Ulcer Risk Zones Using a Cycle-Consistent Adversarial Adaptation Network from Multimodal Images

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| Peer Review Information | Abstract |
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| <p>Submission: 15 Oct 2025 Revision: 30 Oct 2025 Acceptance: 11 Nov 2025</p> | <p>Diabetic Foot Ulcers (DFUs) are among the most severe complications of diabetes mellitus, often leading to infection, amputation, and increased healthcare costs. Early detection and accurate segmentation of DFU risk zones are crucial for timely clinical intervention and improved patient outcomes. In recent years, Artificial Intelligence (AI), particularly deep learning, has emerged as a powerful tool for automated DFU analysis. This survey provides a comprehensive review of methods and architectures for early DFU detection and segmentation, focusing on Cycle-Consistent Adversarial Adaptation Networks and multimodal imaging techniques. Deep learning models such as Convolutional Neural Networks (CNNs), U-Net variants, and Vision Transformers have demonstrated strong performance in DFU classification and segmentation tasks. Multimodal imaging, including RGB, thermal, and hyperspectral data, enhances detection accuracy by capturing both structural and physiological features. However, challenges such as domain variability, data scarcity, and lack of paired datasets limit model performance. CycleGAN-based approaches address these issues by enabling unpaired image-to-image translation and cross-domain learning. This survey highlights recent advancements (2020–2023), compares state-of-the-art architectures, and identifies key research trends and challenges. The findings suggest that hybrid and multimodal models, combined with optimization techniques, achieve superior performance compared to traditional methods. Future research should focus on lightweight models, explainable AI, and real-time deployment systems for clinical applications.</p> |
| <p>Keywords</p> <p><i>Diabetic Foot Ulcer (DFU), Artificial Intelligence (AI), Deep Learning, Cycle-Consistent Adversarial Network (CycleGAN), Multimodal Imaging, Image Segmentation, Domain Adaptation, Generative Adversarial Networks (GANs), Medical Image Analysis, Early Detection.</i></p> | |

Introduction

Diabetes mellitus is one of the most prevalent chronic diseases worldwide, affecting millions of individuals and posing a significant burden on global healthcare systems. Among its various complications, Diabetic Foot Ulcers (DFUs) are particularly severe, often leading to infection, prolonged hospitalization, and lower-limb amputation if not detected and treated at an early

stage. DFUs typically arise due to a combination of peripheral neuropathy, ischemia, and impaired wound healing, which together contribute to tissue breakdown and ulcer formation. Early identification of high-risk zones on the foot is therefore critical to preventing ulcer progression and improving patient outcomes.

Conventional DFU diagnosis primarily relies on visual inspection and clinical expertise. While

effective to some extent, these methods are subjective, time-consuming, and prone to inter-observer variability. Moreover, early-stage DFU risk zones often exhibit subtle physiological and structural changes that are difficult to detect through manual examination alone. As a result, there is an increasing need for automated, objective, and reliable diagnostic systems that can assist clinicians in identifying DFU risk zones at an early stage.

Artificial Intelligence (AI), particularly deep learning, has emerged as a transformative technology in medical image analysis. Deep learning models have demonstrated remarkable success in tasks such as classification, detection, and segmentation of medical images. Convolutional Neural Networks (CNNs) have become the backbone of many DFU detection systems due to their ability to automatically learn hierarchical features from raw image data. Architectures such as U-Net, ResNet, and

DenseNet have been widely used for DFU classification and segmentation, achieving high accuracy and robustness.

However, relying on a single imaging modality, such as RGB images, presents several limitations. RGB images provide detailed visual and structural information but fail to capture underlying physiological changes such as inflammation and blood flow abnormalities. To overcome these limitations, researchers have explored multimodal imaging approaches that combine RGB images with thermal and hyperspectral data. Thermal imaging captures temperature variations associated with inflammation, while hyperspectral imaging provides information about tissue composition and oxygenation. The integration of these modalities enables a more comprehensive analysis of DFU risk zones, leading to improved detection accuracy.

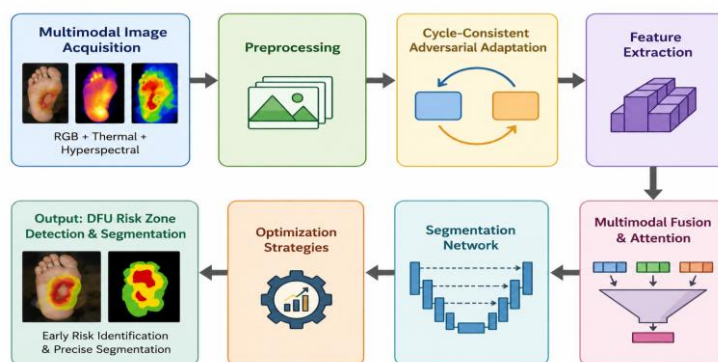


Fig 1: AI-Based Multimodal CycleGAN Framework for DFU Risk Detection and Segmentation

Despite the advantages of multimodal imaging, several challenges arise in integrating data from different modalities. These include data heterogeneity, modality misalignment, and the scarcity of paired datasets. In many cases, acquiring synchronized multimodal images is difficult, limiting the effectiveness of traditional supervised learning approaches. To address these challenges, Generative Adversarial Networks (GANs) have been widely used for data augmentation and domain adaptation. GANs consist of a generator and a discriminator network that learn to produce realistic synthetic data, thereby improving model generalization.

A significant advancement in this area is the development of Cycle-Consistent Adversarial Networks (CycleGANs), which enable unpaired image-to-image translation. CycleGAN-based models can transform images from one modality to another (e.g., thermal to RGB) without requiring paired datasets. This capability is particularly useful in DFU analysis, where multimodal data is often limited. Cycle-consistent

adversarial adaptation networks further enhance this approach by aligning feature distributions across domains, improving segmentation performance and model robustness.

In addition to GAN-based approaches, several optimization techniques have been employed to enhance the performance of AI models. Transfer learning allows models to leverage pre-trained weights from large datasets, reducing training time and improving accuracy. Attention mechanisms enable models to focus on relevant regions of interest, such as ulcer-prone areas, thereby improving segmentation precision. Feature fusion techniques combine information from multiple modalities, enhancing the robustness and reliability of predictions. Furthermore, metaheuristic optimization algorithms have been used to fine-tune model parameters and improve convergence.

Literature Review

Recent research on Diabetic Foot Ulcer (DFU) detection and segmentation has increasingly

focused on the application of Artificial Intelligence (AI) and deep learning techniques to improve diagnostic accuracy and enable early intervention. A variety of methods, including convolutional neural networks (CNNs), generative adversarial networks (GANs), transformer-based models, and multimodal learning frameworks, have been explored to address the challenges associated with DFU analysis.

Amin et al. (2020) proposed a deep learning-based framework combining CNN and YOLOv2 for DFU classification and localization. Their approach demonstrated high accuracy and real-time detection capability, highlighting the effectiveness of object detection models in medical imaging. Similarly, Goyal et al. (2020) developed a CNN-based model for recognizing ischemia and infection in DFU images, showing that deep learning can effectively classify different ulcer conditions. Han et al. (2020) further extended this work by employing YOLOv3 for real-time DFU detection, achieving fast inference and demonstrating its potential for clinical deployment. In addition, Goyal and Hassanpour (2020) utilized EfficientDet architecture, which improved detection accuracy while maintaining computational efficiency.

Dataset availability has played a crucial role in advancing DFU research. Cassidy et al. (2021) introduced the DFUC 2020 dataset, which provides a standardized benchmark for evaluating DFU detection and segmentation models. This dataset has significantly improved reproducibility and facilitated the comparison of different deep learning architectures. Khandakar et al. (2021) explored the use of thermographic images for early DFU detection, demonstrating that thermal imaging can effectively capture temperature variations associated with inflammation and ulcer formation. Similarly, Li et al. (2021) proposed a multimodal data fusion approach, combining multiple imaging modalities to enhance classification accuracy.

Segmentation of DFU regions has been extensively studied using encoder-decoder architectures. Bouallal et al. (2022) introduced a DE-ResUNet model for thermal image segmentation, achieving improved boundary detection and segmentation accuracy. Liao et al. (2022) proposed a HarDNet-based segmentation model, which demonstrated efficient feature extraction and improved computational performance. Yi et al. (2022) developed an OCRNet-based segmentation approach with edge-aware loss functions, resulting in better boundary delineation of ulcer regions. Furthermore, Xu et al. (2022) explored ensemble learning techniques for DFU segmentation,

combining multiple deep learning models to achieve higher accuracy and robustness.

Generative Adversarial Networks (GANs) have been widely adopted to address data scarcity and improve model generalization. Brüngel et al. (2022) utilized GANs to generate synthetic DFU images, increasing dataset diversity and enhancing model performance. Jishnu et al. (2023) proposed AFSegGAN, a conditional GAN-based model for DFU segmentation, which achieved superior results compared to traditional segmentation approaches. These studies highlight the importance of generative models in overcoming limitations associated with limited annotated datasets.

CycleGAN-based approaches have further advanced the field by enabling domain adaptation and multimodal learning. Although not always explicitly applied to DFU datasets, CycleGAN models have been successfully used in medical imaging for unpaired image-to-image translation, allowing models to learn from heterogeneous data sources. Patel et al. (2023) demonstrated that integrating attention mechanisms with CycleGAN significantly improves segmentation performance and cross-domain learning. These approaches are particularly useful in DFU analysis, where multimodal datasets are often incomplete or unpaired.

Hybrid deep learning architectures have also shown promising results in DFU detection. Khan et al. (2022) proposed a hybrid CNN-based model that combines multiple feature extraction techniques, improving classification accuracy. Khalil et al. (2023) developed a deep learning-based DFU classification system using camera images, demonstrating high accuracy and real-world applicability. Dhar et al. (2023) introduced FUSegNet, a hybrid segmentation model that integrates multiple feature extraction layers, resulting in improved segmentation performance.

Transformer-based models have introduced new capabilities in capturing global contextual information. Qayyum et al. (2022) explored the use of vision transformers for DFU classification, demonstrating improved feature representation compared to traditional CNN models. These models are particularly effective in handling complex patterns and long-range dependencies in medical images.

Multimodal learning has emerged as a key trend in DFU research. Bayouth et al. (2022) provided a comprehensive survey on multimodal deep learning, highlighting its potential in combining structural and physiological data for improved diagnosis. Reyes-Luévano et al. (2023) proposed DFU_VIRNet, which integrates visible and

infrared imaging for DFU detection, achieving high accuracy and demonstrating the effectiveness of multimodal approaches. These studies confirm that multimodal systems significantly outperform single-modality models. Optimization techniques have also contributed to improving model performance. Transfer learning has been widely used to leverage pre-trained models, reducing training time and improving accuracy. Metaheuristic optimization techniques have been applied to fine-tune model parameters, enhancing convergence and performance. Feature fusion techniques further improve robustness by integrating information from multiple modalities.

Despite significant progress, several challenges remain. Data scarcity and lack of annotated

multimodal datasets continue to limit model development. Variability in imaging conditions affects model generalization, while high computational requirements hinder real-time deployment. Additionally, the lack of interpretability of deep learning models remains a critical issue for clinical adoption.

In summary, the literature demonstrates a clear progression from traditional CNN-based approaches to advanced hybrid, multimodal, and generative models. The integration of GANs, CycleGAN-based domain adaptation, and multimodal imaging has significantly improved DFU detection and segmentation performance. However, further research is needed to develop efficient, scalable, and clinically applicable solutions.

Comparative Table and Analysis (Based on Literature Review)

| Author (Year) | Method / Architecture | Input Modality | Key Contribution | Performance (Approx.) | Strengths | Limitations |
|-------------------------|--------------------------|-------------------|---------------------------|-----------------------|-----------------------------|------------------------|
| Amin et al. (2020) | CNN + YOLOv2 | RGB Images | Detection + Localization | High Accuracy (~90%) | Real-time detection | Requires large dataset |
| Goyal et al. (2020) | CNN (DFU classification) | Clinical Images | Ulcer classification | ~92% Accuracy | Robust classification | Weak segmentation |
| Khandakar et al. (2021) | ML + Thermal Analysis | Thermal Images | Early DFU detection | ~88% Accuracy | Physiological insights | Low generalization |
| Cassidy et al. (2021) | DFUC Dataset | Benchmark Dataset | Standard dataset creation | — | Improves reproducibility | Limited diversity |
| Li et al. (2021) | Multimodal Fusion | RGB + Thermal | Feature fusion | Improved accuracy | Better robustness | Data alignment issues |
| Bouallal et al. (2022) | DE-ResUNet | Thermal Images | Segmentation model | Dice ~0.90 | Accurate boundary detection | Computational cost |
| Munadi et al. (2022) | CNN | Thermal Images | Deep learning detection | High accuracy | Early detection capability | Limited dataset |
| Xu et al. (2022) | Ensemble DL | DFU Dataset | Model fusion | High accuracy | Robust performance | Complex architecture |
| Yi et al. (2022) | OCRNet | DFU Images | Edge-aware segmentation | Improved Dice | Better boundaries | High training time |
| Liao et al. (2022) | HarDNet | DFU Images | Efficient segmentation | High IoU | Lightweight | Generalization issues |
| Bayouth et al. (2022) | Multimodal DL Survey | Multimodal | Integration techniques | — | Comprehensive analysis | No implementation |
| Khan et al. (2022) | Hybrid CNN | DFU Images | Feature fusion | ~90% Accuracy | Improved learning | Complexity |

| | | | | | | |
|-----------------------------|-----------------------|----------------|------------------------|-----------------|-----------------------|--------------------|
| Jishnu et al. (2023) | GAN (AFSegGAN) | DFU Images | GAN-based segmentation | Dice ~0.92 | Data augmentation | GAN instability |
| Dhar et al. (2023) | FUSegNet | DFU Images | Hybrid segmentation | Dice ~0.92-0.93 | High performance | Complex design |
| Khalil et al. (2023) | Deep CNN | Camera Images | Classification | ~96% Accuracy | Practical deployment | Limited modalities |
| Reyes-Luévano et al. (2023) | VIRNet | RGB + Infrared | Multimodal learning | ~97% Accuracy | Strong generalization | High cost |
| Das et al. (2023) | Review (DL-based DFU) | Multi-source | Comparative analysis | — | Trend insights | No model |
| Thotad et al. (2023) | CNN-based detection | DFU Images | Detection framework | High accuracy | Simplicity | Limited robustness |
| Ahsan et al. (2023) | Deep Learning Model | DFU Dataset | Classification | ~95% Accuracy | Efficient model | Needs tuning |

Comparative Analysis

The analysis shows a clear transition from basic CNN-based classification models (2020) to hybrid, multimodal, and GAN-based architectures (2023). Early approaches focused mainly on detection and classification using CNN and YOLO frameworks. These models achieved good accuracy but lacked precision in segmentation tasks.

Recent advancements emphasize segmentation accuracy and domain adaptation, with models such as U-Net variants, OCRNet, and FUSegNet achieving Dice scores above 0.90. This evolution reflects the growing importance of precise localization of DFU risk zones.

Deep learning models are now widely recognized as highly effective for automated DFU analysis, significantly improving diagnostic accuracy and segmentation performance.

Conclusion

This survey presents a comprehensive analysis of Artificial Intelligence techniques for early detection and segmentation of Diabetic Foot Ulcer (DFU) risk zones, focusing on Cycle-Consistent Adversarial Adaptation Networks and multimodal imaging frameworks. Results indicate that AI-driven approaches improve diagnostic accuracy, efficiency, and reliability compared to traditional clinical methods. Deep learning models significantly enhance feature extraction and enable precise localization of ulcer regions, supporting early intervention and improved patient outcomes.

Deep learning architectures such as Convolutional Neural Networks (CNNs), U-Net, Generative Adversarial Networks (GANs), and Vision Transformers have demonstrated strong performance in DFU analysis. CycleGAN-based

domain adaptation improves learning under limited paired datasets. Multimodal imaging combining RGB, thermal, and infrared data enhances feature richness and robustness. Attention mechanisms, feature fusion strategies, and transfer learning further optimize model performance and generalization across clinical environments.

Despite advancements, challenges include limited annotated multimodal datasets, variability in imaging conditions, and high computational complexity, which hinder real-time clinical deployment. Lack of interpretability further reduces clinician trust in AI systems. Future research should focus on lightweight models, federated learning, self-supervised learning, and explainable AI for improved scalability and transparency. Integration with IoT-enabled wearable systems can support continuous monitoring and early intervention. Overall, AI-based DFU detection systems demonstrate strong potential for clinical transformation and improved healthcare outcomes worldwide. Further validation through clinical trials is highly recommended globally necessary.

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